Processing Polysomnographic Signals, using Independent Component Analysis

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PROCESSING POLYSOMNOGRAPHIC SIGNALS, USING INDEPENDENT COMPONENT ANALYSIS APPROACHES

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Abstract:

In this paper several applications of the Independent Component Analysis (ICA) algorithm, for the analysis of biomedical signal recordings have been investigated. One of these applications is the removal of EEG artifacts such as the EOG. It is shown that ICA may serve as a powerful tool, which could help the analysis of biomedical recordings, and give better insights about the underlying sources of some disorders. Another application of the proposed method is the detection of sleep disorders in patients suffering from sleep apnea. The ultimate goal of this approach is to develop an automatic noninvasive data acquisition system, for clinical applications.

Key Words:

Polysomnographic signals, Independent Component Analysis, Biomedical signal artifacts.

Introduction:

A. Blind Source Separation

Blind Source Separation (BSS) is a general term referring to many signal processing techniques which extract sources (signals) from a set of recordings (observations). One of these methods is known as Independent Component Analysis (ICA) [1]. The simple linear model of ICA and the practically feasible constraints that it imposes on the sources has made ICA a good candidate for many applied source separation problems. In the recent years it has been shown that one of the most promising applications of ICA is the field of *Biomedical Signal Processing* [2]. Biomedical signals such as the *electroencephalogram* (EEG) are characterized by their low signal-to-noise ratio (SNR), where the so called noise consists of environmental noises such as the 50 or 60 Hz line noise, artifacts caused by subject movement and electrode displacement, and other biomedical signal sources such as the ECG, EMG and etc. A disappointing fact about these noises and artifacts is that they usually overlap the original signal in the frequency domain; which makes most of the conventional spectral noise-cancellation methods useless.

On the other hand, from a clinical point of view, non-invasive methods of biomedical signal recordings are preferred to their invasive counterparts. So in practice the sensors are quite distanced from the desired source and consequently the electrodes receive the desired signal(s), pooled within mixtures of unwanted noises and artifacts, which have all together been mixed and attenuated through out the so called *volume conductor*. Taking all these facts into consideration, methods such as the ICA may be used, in order to extract the most possible information from the sensor recordings without the need of invasive methods.

B. An overview of ICA

ICA has been well noted in the literature ([1], [3]) and several models have been presented for it in the previous years. One of the most popular models of ICA, is based on a simple linear model, and starts by assuming N signal sources ($s_i(t)$, $i=1,2,\ldots,N$), generating signals in an environment, and as many sensors ($x_i(t)$ $i=1,2,\ldots,N$), recording superpositions of the produced signals. Accordingly each sensor receives a mixture of the signals, depending on its distance from the sources. Assuming a linear model for the environment, the problem may be formulated as:

$$\underline{X} = A.\underline{S} \tag{1}$$

where $\underline{S}=[s_1(t),s_2(t),\ldots,s_N(t)]^T$ and $\underline{X}=[x_1(t),x_2(t),\ldots,x_N(t)]^T$ are vectors containing the sources and recorded (observation) signals respectively, and A is the *mixing matrix* which depends on the location of the sensors and the attenuation of each signal before reaching the sensors. In this case, our goal is to somehow recover the sources from the observation signals by estimating the mixing matrix. If we represent the i^{th} column of A with the vector $\underline{a}_i$, equation (1) may be expanded as:

$$\underline{X}=\underline{a}_1 s_1(t) + \underline{a}_2 s_2(t) + \ldots + \underline{a}_N s_N(t). \quad (2)$$

In order to solve this problem, ICA assumes that the sources $s_i(t)$ are *statistically independent* with a *non-gaussian* probability distribution function (pdf). In the first view it may seem that estimating the sources without knowing the mixing matrix is not possible; but in fact it has been shown that the two constraints imposed on the model are enough for solving the problem, except for the sign and permutation of the sources [1].

Intuitively speaking, the central limit theorem demands that the distribution of the summation of two or more independent sources be *more Gaussian* than each of the sources. So the distribution of signals recorded from the sensors $x_i(t)$ tends to a Gaussian distribution, as the number of sources increase. Apparently when we speak about a distribution being *more Gaussian* than another, a measure of Gaussianity is needed. By now several of these measures, such as the Kurtosis and Negentropy have been introduced and utilized in ICA applications. Having such a measure, the basic idea of ICA would be to find the most non-gaussian distribution for the sources. Of course approaches other than finding non-Gaussian distributions, such as the *Information Maximization* (Infomax), or *Maximum Likelihood* (ML) approach have also been introduced; but it has been shown that all these approaches finally extract the most non-gaussian set of the mixing sources.

One of the most popular algorithms which have been proposed for ICA is the fixed-point ICA algorithm designed by Hyvarinen [1]. Based on this algorithm the FastICA software package has been implemented; which uses a recursive procedure in order to estimate the mixing matrix and extracting the independent components from the given signals [4].

As it was noted, ICA assumes the sources being statistically independent. Although independence is a strong mathematical constraint, but for many physical problems it may be fulfilled; specially that in practice when using algorithm such as FastICA, each time a small segment of the data set is given to the algorithm, which may be assumed locally independent.

Methodology:

A. Data Collection

The data is a standard polysomnographic recording acquired from patients suffering from *sleep apnea* disorders, during 2 hours of sleep. Among the 23 recorded channels, those of interest for our study are 10 EEG channels recorded from the leads: C_3, C_4, O_1, O_2, FP_1, FP_2, T_3, T_4, F_7 and F_8 according to the 10-20 International System (figure 1), 2 EOG channels from the left and right eyes, an air flow(flux), ECG and EMG channel. The data was collected via the DELTAMED COHERENCE® 3NT system, using 256 Hz as the sampling rate, and transferred to a PC for off-line analysis. Further analysis of the data was performed using Matlab®.

Due to the long duration of the recordings, the data was segmented into 10(sec.) epochs and the FastICA was applied to each segment. In fact in a period of 10 seconds the EEG signal is quite stationary, and ICA can give rather good results. This duration of data has experimentally been approved and reported in previous works [2].

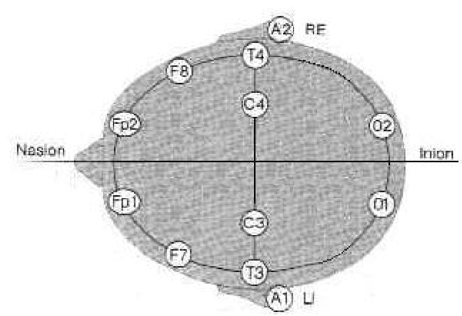

Figure (1) The electrode configuration used for recording EEG signals

B. EEG Artifact Removal

The first application of ICA, which we analyzed, was the removal of EOG artifacts from EEG signals. It is known that eye movement and eye blinks are one of the major artifacts of EEG signals. Although the recordings were taken from a patient during sleep, where eye blinks are of less consideration, eye movements (saccades) and sudden blinks, specially during the apnea epochs of the sleep, cause considerable artifacts on the EEG measurements. For this analysis two different approaches were adopted. In the first approach, each EEG channel from the left/right hemispher electrodes were taken with the EOG channels recorded from the rigth/left eyes respectively, and given to the FastICA algorithm separately. In this case, the outputs of the algorithm consisted of two extracted sources. The correlation of these two sources with the two input channels was calculated, and the source being more correlated with the initial EEG channel was chosen as the *cleaned* EEG source. Note that in computing these correlation values, due to the shortcoming of the ICA algorithm in estimating the sign of the sources, the absolute value of the correlation was assumed. The underlying assumption of this method is the existence of an EOG source, which acts independently from the true EEG sources.

The second approach was to give all the EEG channels recorded from the left/right hemispher, with the EOG channel of the oposite side (rigth/left eye) to the ICA algorithm at the same time. In this method after the computation of the Independent sources and the mixing matrix A, the correlation of these sources was computed with respect to the input EOG channel. In this method which was quite alike the previously reported work in [2], the channel which is most correlated with the input EOG is assumed to be the EOG source, and in order to eliminate its effect from other EEG channels, according to Eq. (2), it is enough to set the column of the mixing matrix A, which corresponds to the extracted EOG source to zero and multiply the new matrix A in the extracted sources. By this way the effect of the EOG source is eliminated from the EEG recordings and we attain *pure* EEG channels. The underlying assumptions of this method are more restricting than those of the first method. In fact in this method we have assumed several EEG sources and an EOG source inside the brain, which are all non-gaussian and statistically independent.

C. Source Extraction

Another approach was to give all the different channels such as the EEG, EOG and ECG to the FastICA algorithm. By this way several sources were extracted, some of which corresponded to well known physiological sources, such as the heart rate, and others refer to other independent sources which may have other hidden physiological sources or may be caused by an artifact or environmental noise.

Discussion:

According to the methods explained in the previous section, ICA may be used for the elimination of EOG artifacts from EEG recordings; but it should be noted that the underlying assumption of these methods, which assume several independent EEG and EOG sources inside the brain, is questionable. Although, according to the explained methods, it may not be necessary to find a direct interpretation for the extracted sources; since after extracting them, and eliminating the EOG sources, the original EEG channels are achieved by multiplying the extracted sources by the mixing matrix.

In order to use these methods, as a means of detecting and analyzing *sleep disorders*, the polysomnographic data may be visually analyzed and the epochs containing an apnea disorder, be extracted from the data set. By giving these epochs to the ICA algorithm, several sources will be extracted, which do not necessarily correspond to any specific channel, but in fact refer to hidden sources, or patterns which may be the underlying basis for apnea. By detecting such sources a better insight of apnea mechanism would be achieved.

Another important consideration about using ICA for such applications is the fact that when the sources are not truly *independent* or have *Gaussian* distributions, it is very likely for the ICA algorithm to extract components from a single channel, instead of separating the sources. This is specially the case in applications with a few channels of recordings [5]. Of course this feature of ICA may be desirable in some cases (e.g. for extracting independent components from a single channel of data); but for other applications such as the elimination of EOG artifacts this point may not be what is expected, and the problem may easily be un-noticed, since there is no strict way of classifying a true EEG source from a fake one.

Conclusion:

In this paper several methods based on the *Independent Component Analysis* method were presented for artifact removal and analysis of polysomnographic recordings. The key feature of this approach is that it provides a noninvasive data analysis method, which may be used for both the elimination of artifacts/noises from the recordings, and at the same time finding the underlying sources of the acquired data. This approach may be used in a real-time, automated diagnosis system with many clinical applications such as the detection of sleep disorders such as *apnea* (figure 2).

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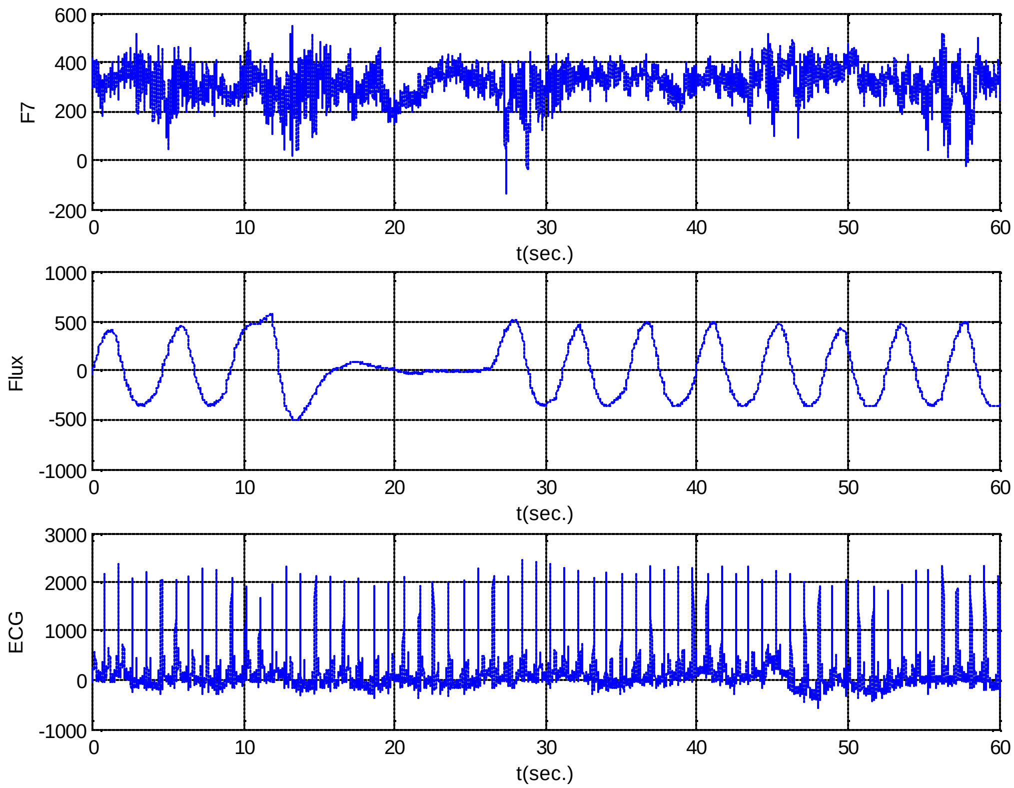

Figure (2) A one minute epoch of three recorded channels containing a breathing disorder. The data has been recorded from a patient suffering from sleep-apnea, during sleep.